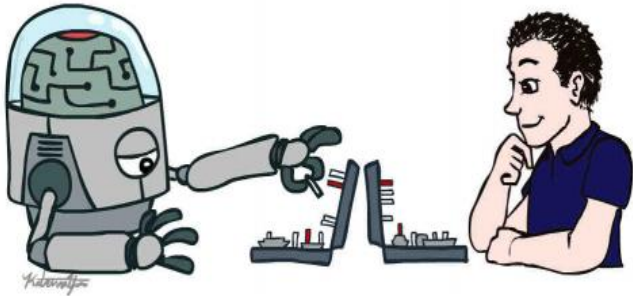
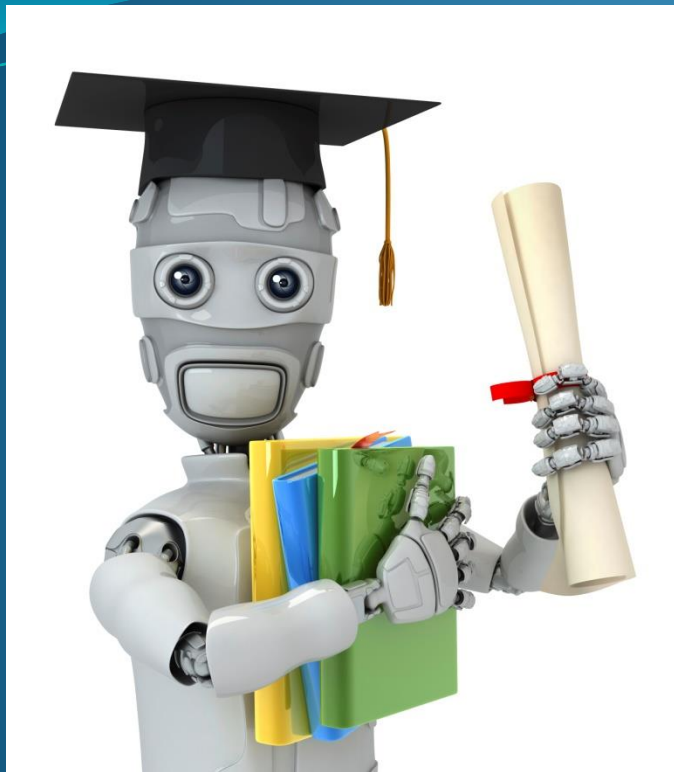


# Artificial Intelligence

## Part I: Machine learning





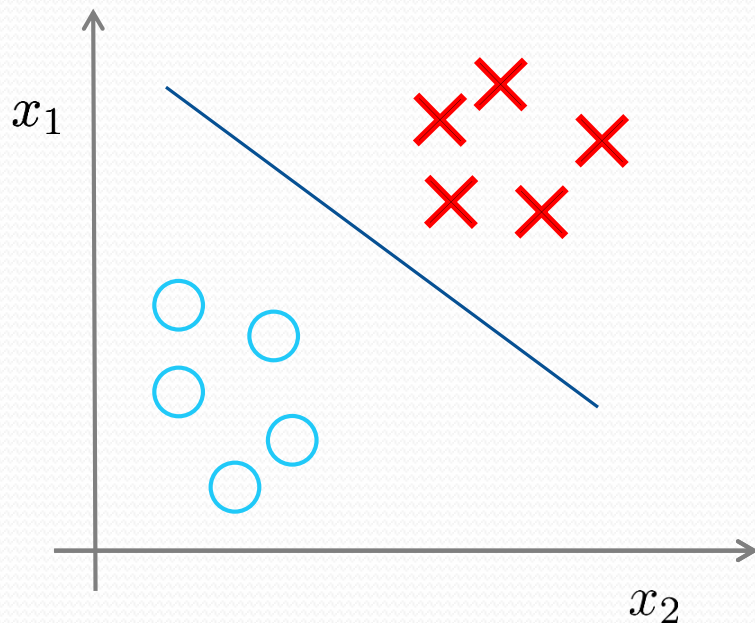
Machine Learning

# Clustering

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Unsupervised learning  
introduction

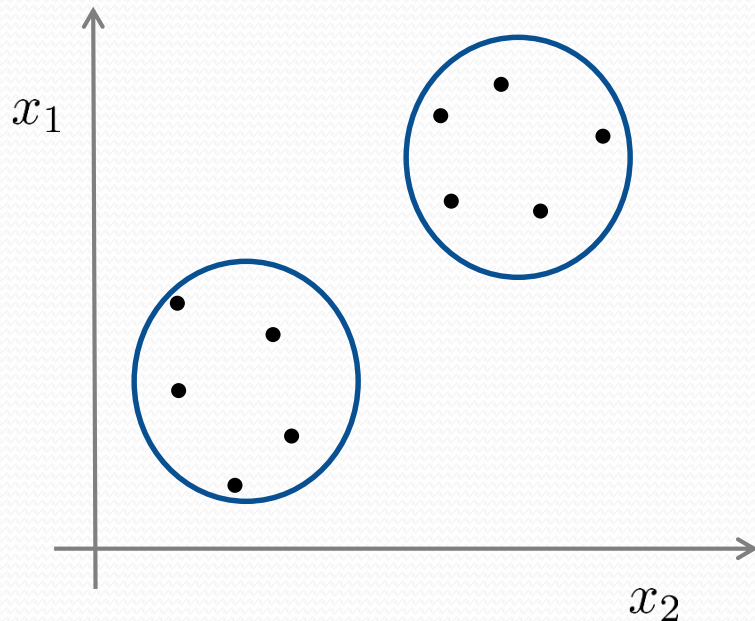
# Supervised learning



Given labeled training set:

$$\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), (x^{(3)}, y^{(3)}), \dots, (x^{(m)}, y^{(m)})\}$$

# Unsupervised learning

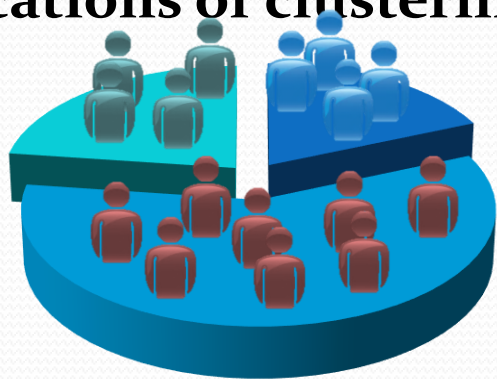


Clustering algorithm:  
group these data into two  
different clusters.

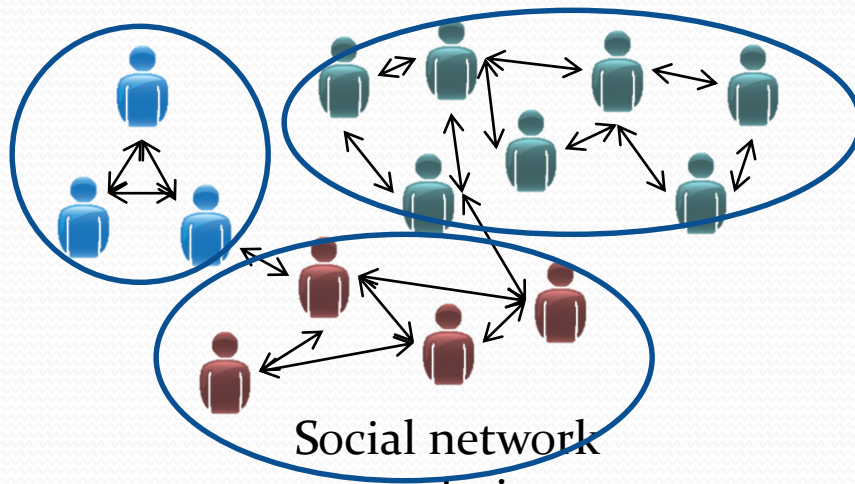
Given unlabeled training set:  $\{x^{(1)}, x^{(2)}, x^{(3)}, \dots, x^{(m)}\}$



# Applications of clustering



Market segmentation



Social network



Organize computing clusters

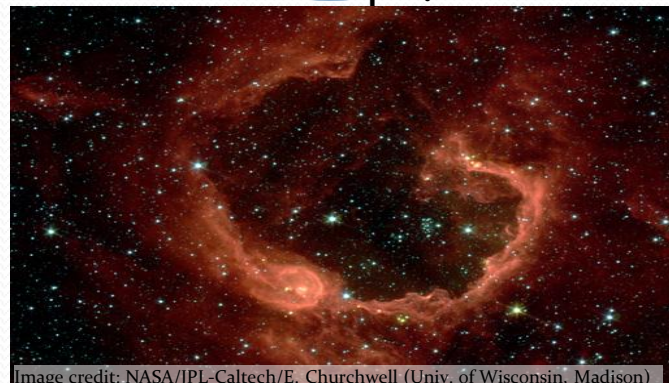
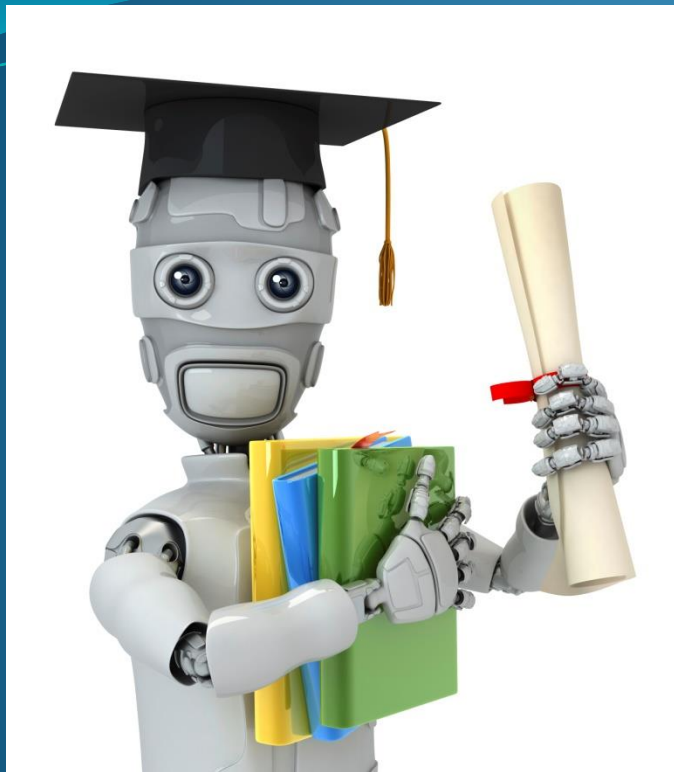


Image credit: NASA/JPL-Caltech/E. Churchwell (Univ. of Wisconsin, Madison)

Astronomical data analysis




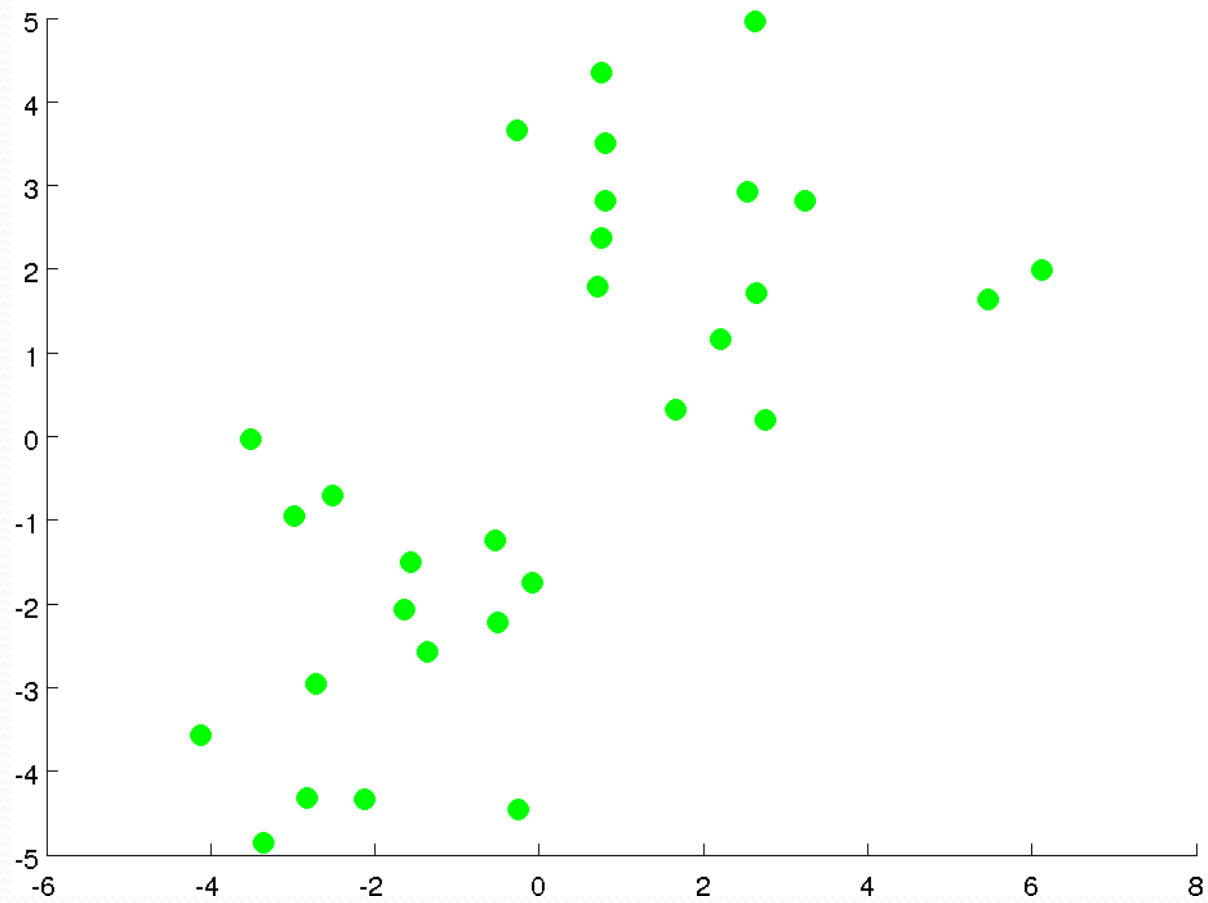
Machine Learning

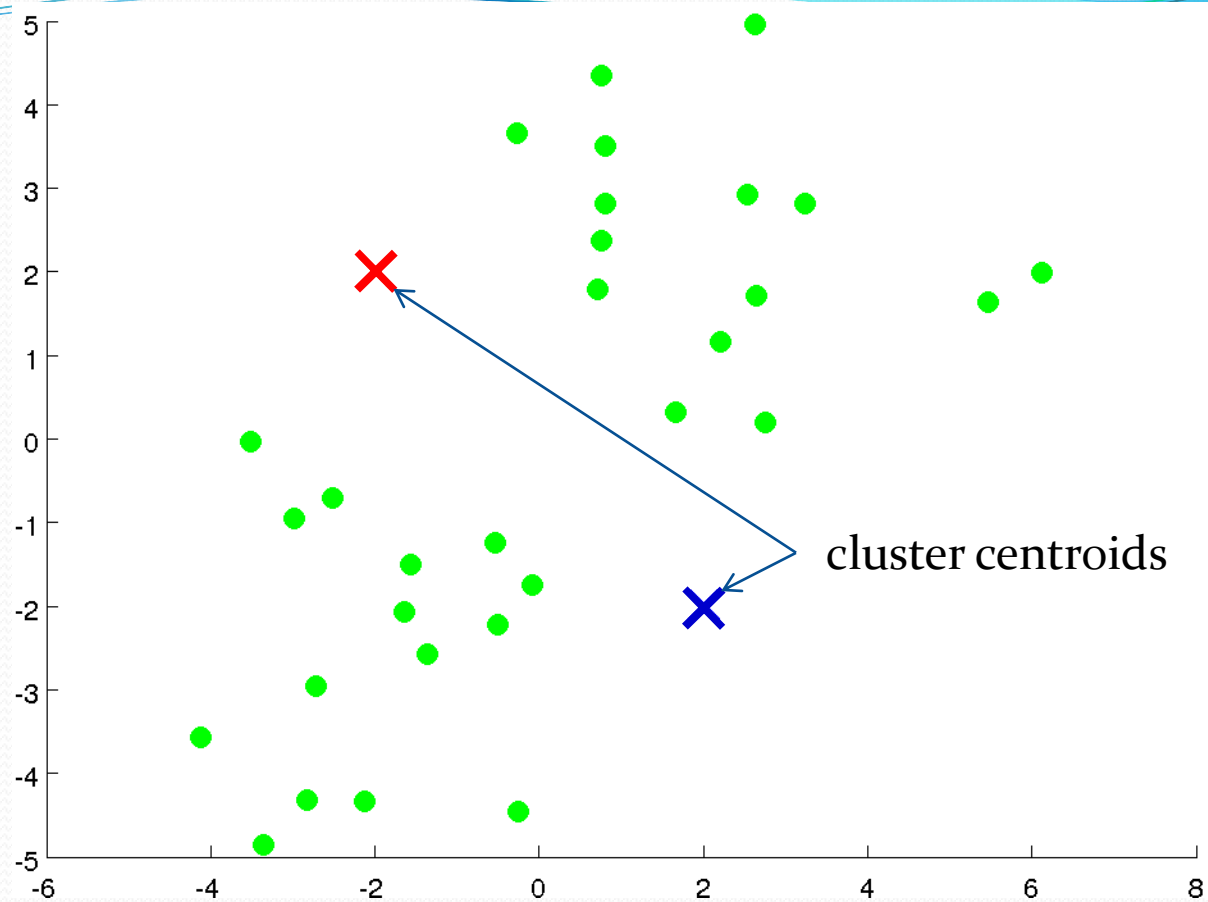
# Clustering

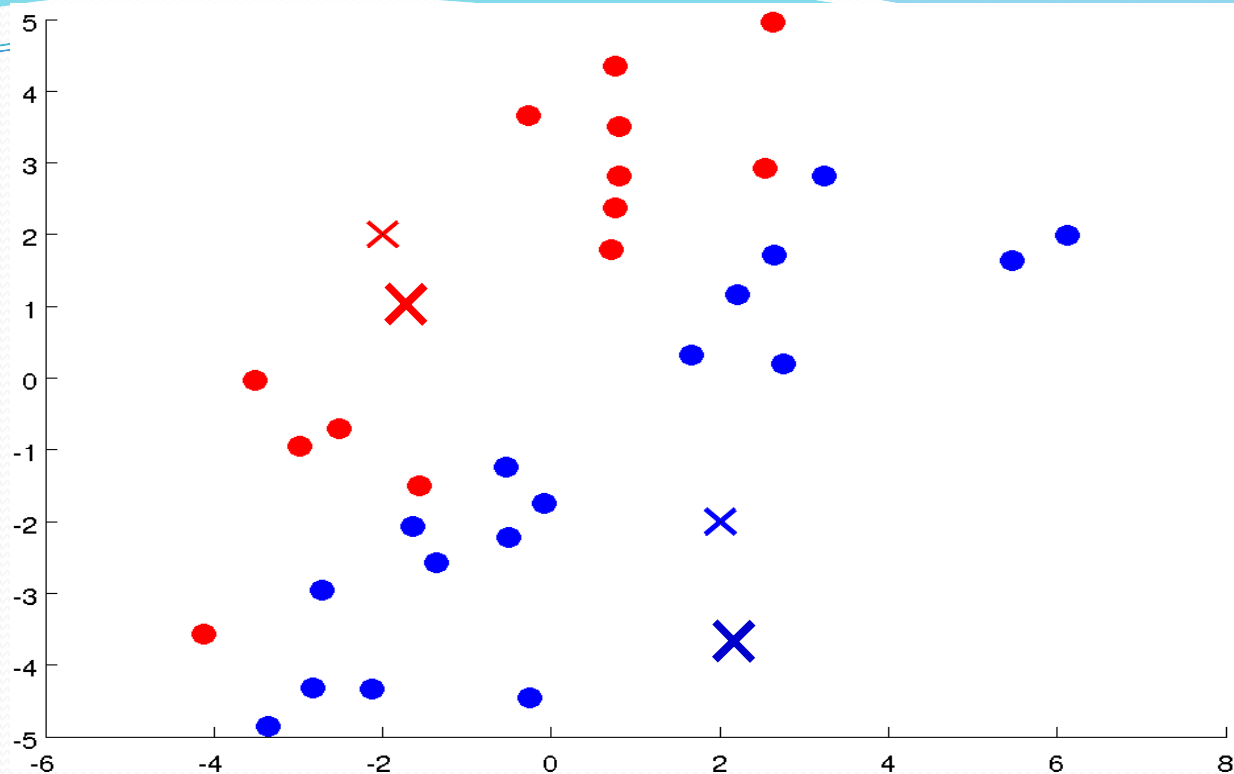
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## K-means algorithm

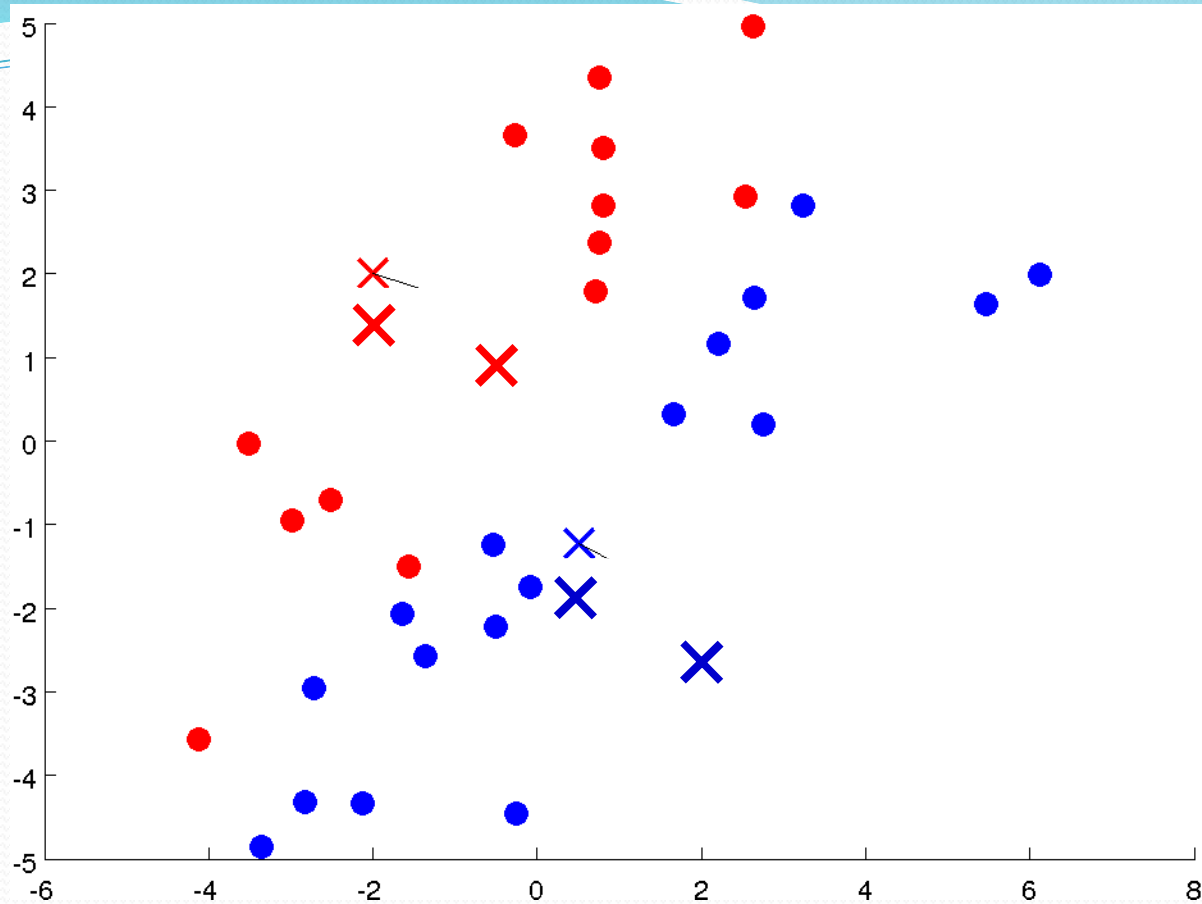
- 
- The K Means algorithm is by far the most widely used clustering algorithm.
  - K Means is an iterative algorithm and it does two things. First is a cluster assignment step, and second is a move centroid step.



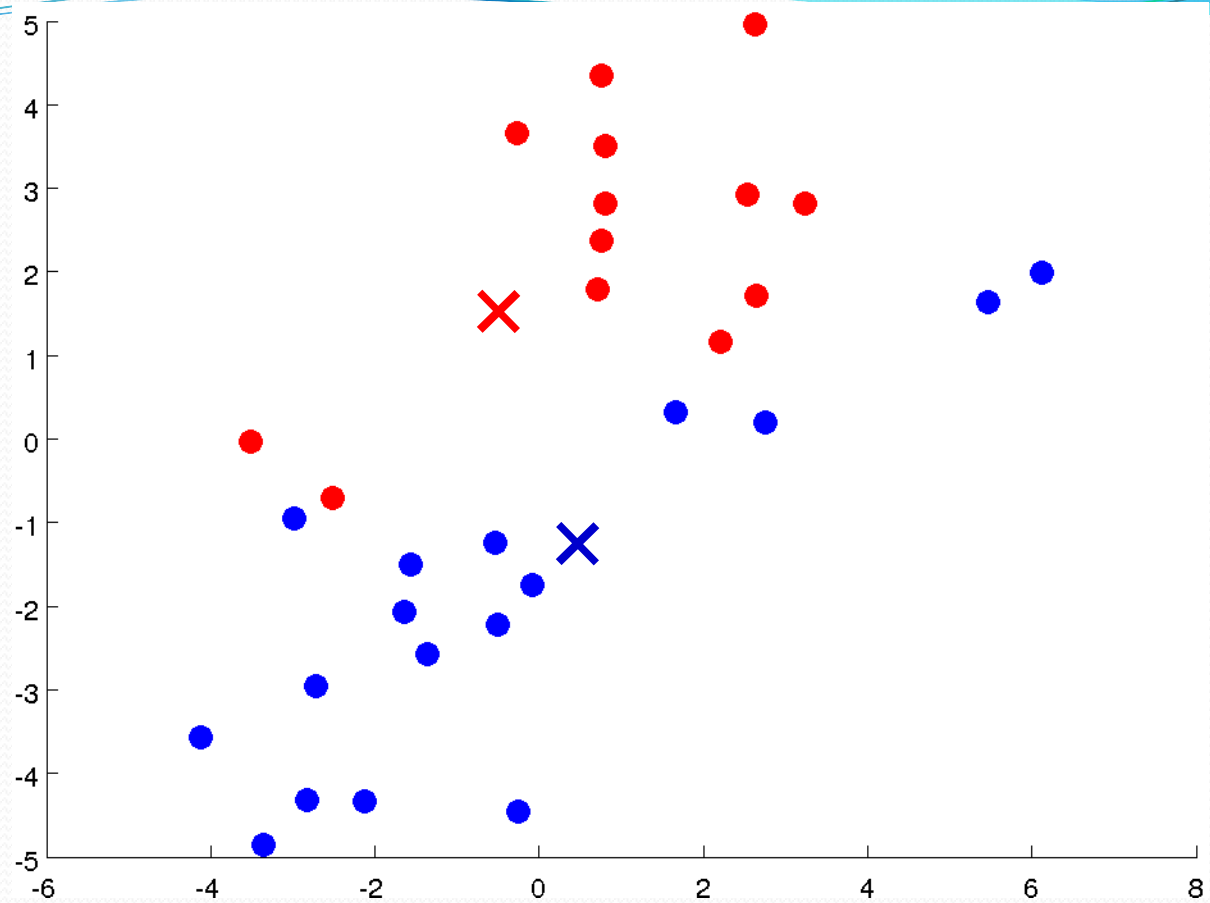




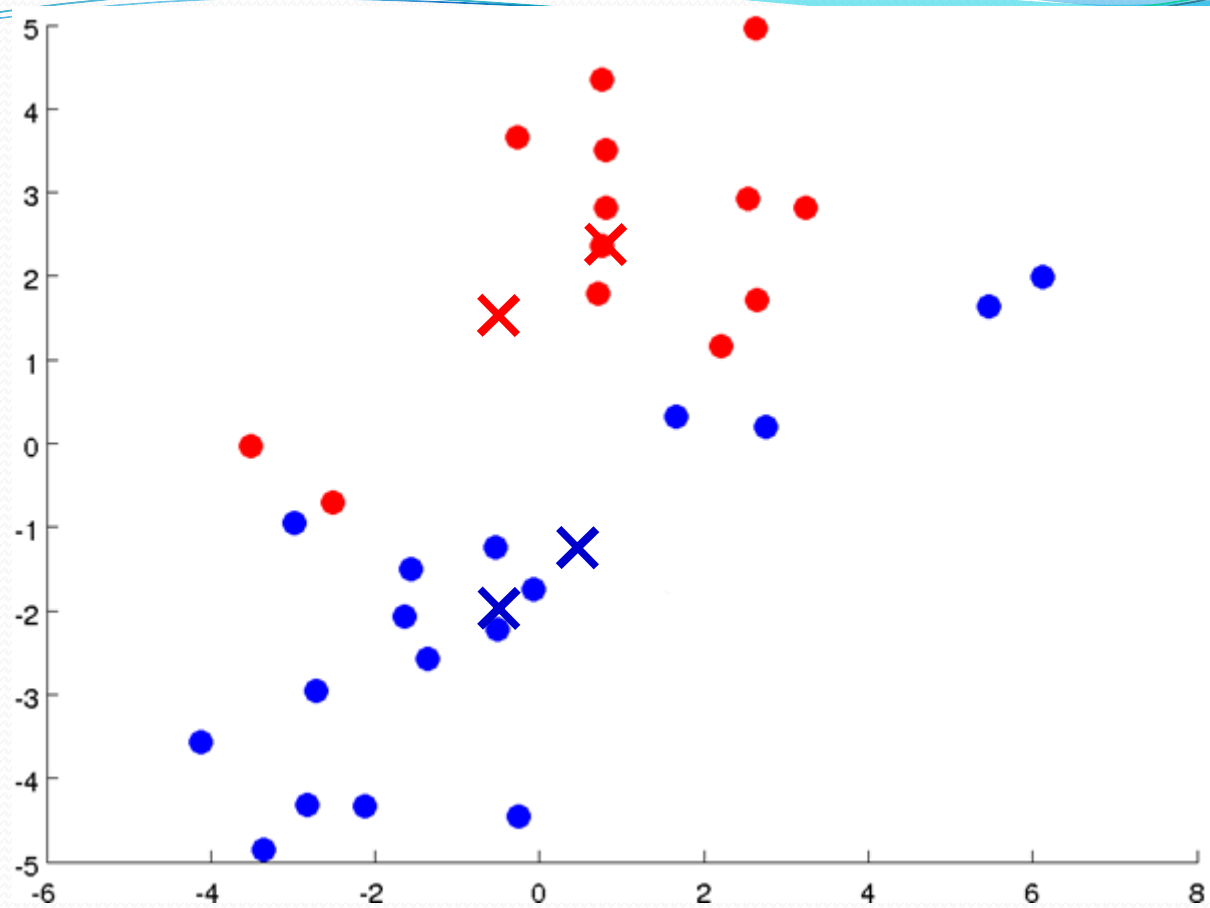
➤ In the cluster assignment step, the algorithm goes through each of the training examples, and depending on whether it's closer to which cluster centroid, it is going to assign each of the data points to one of the two cluster centroids.

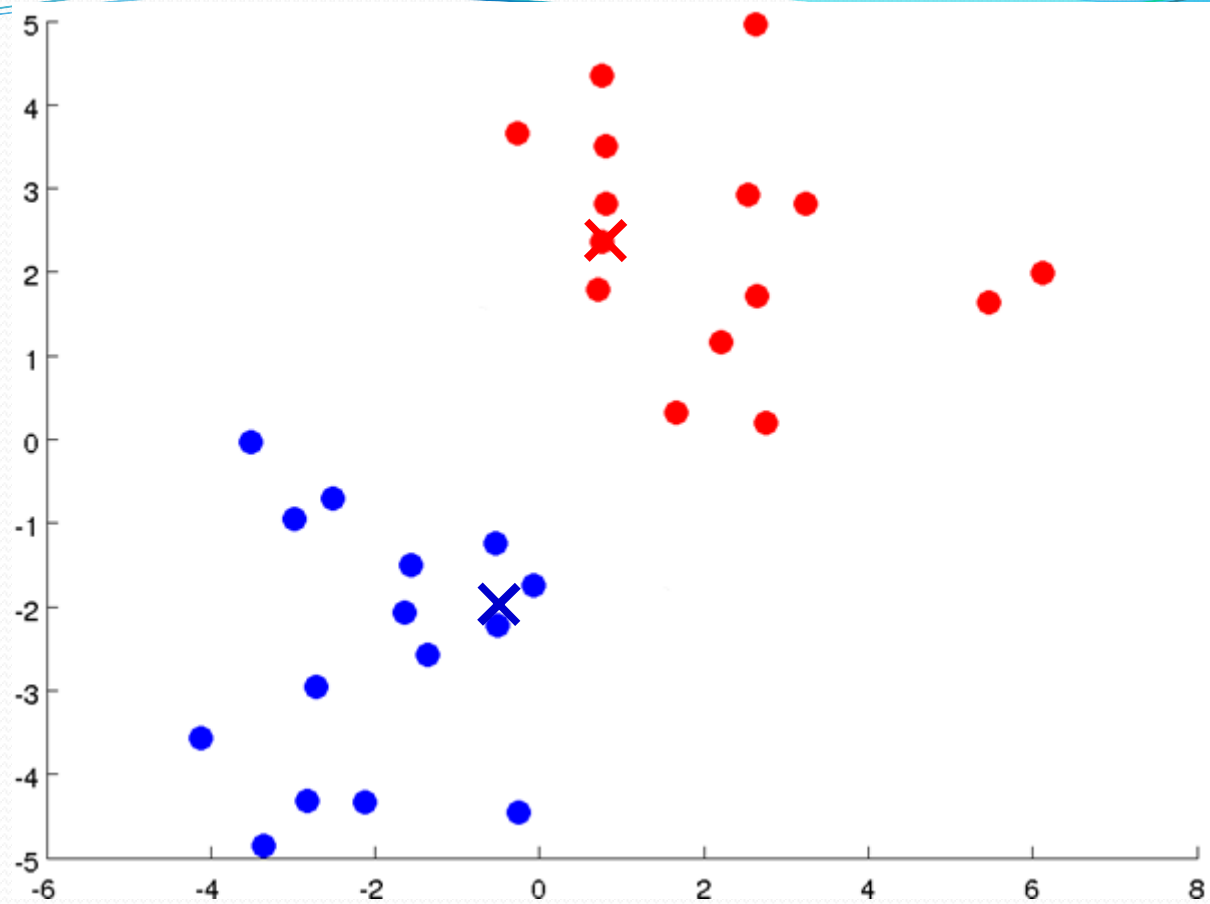


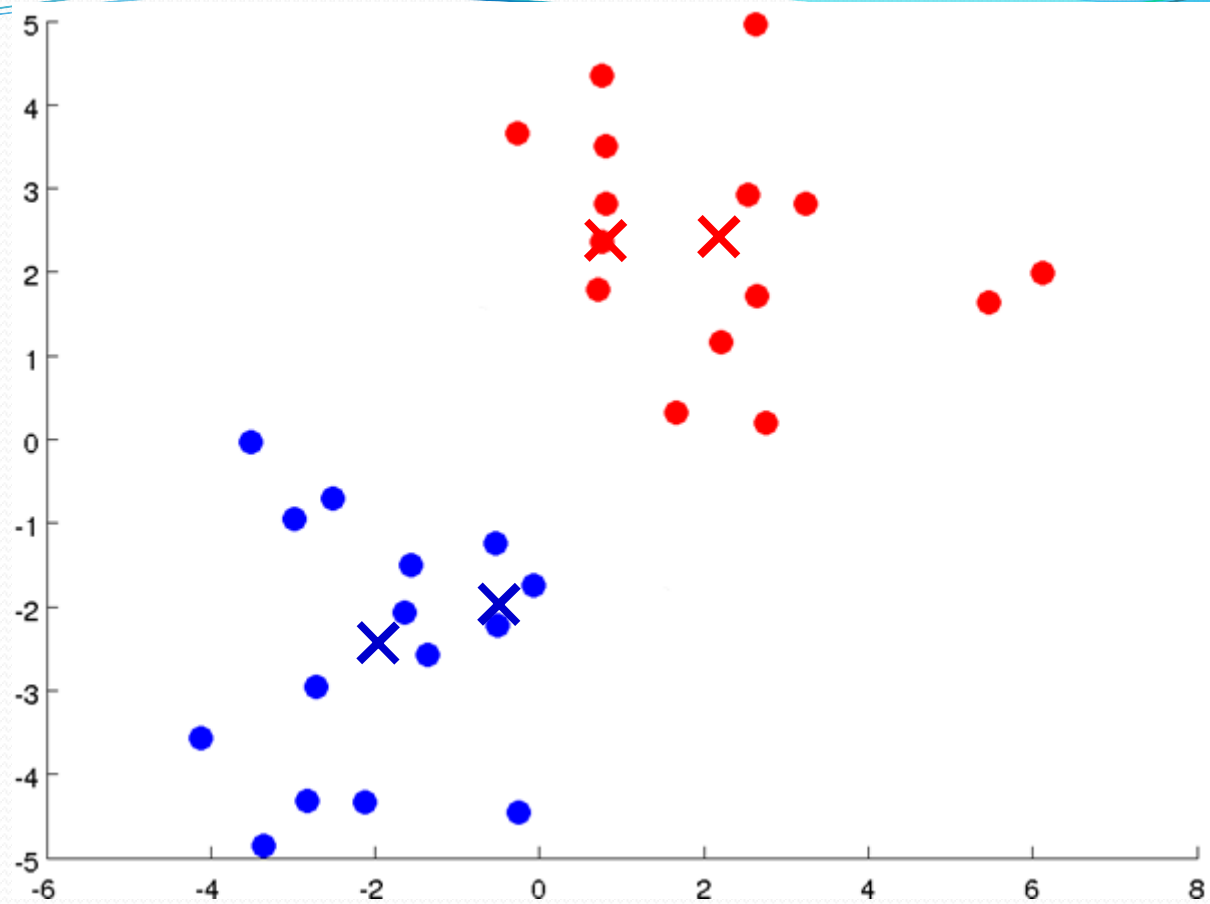
➤ In the move centroid step, the algorithm is going to move the two cluster centroids to the average of the points of the same cluster.

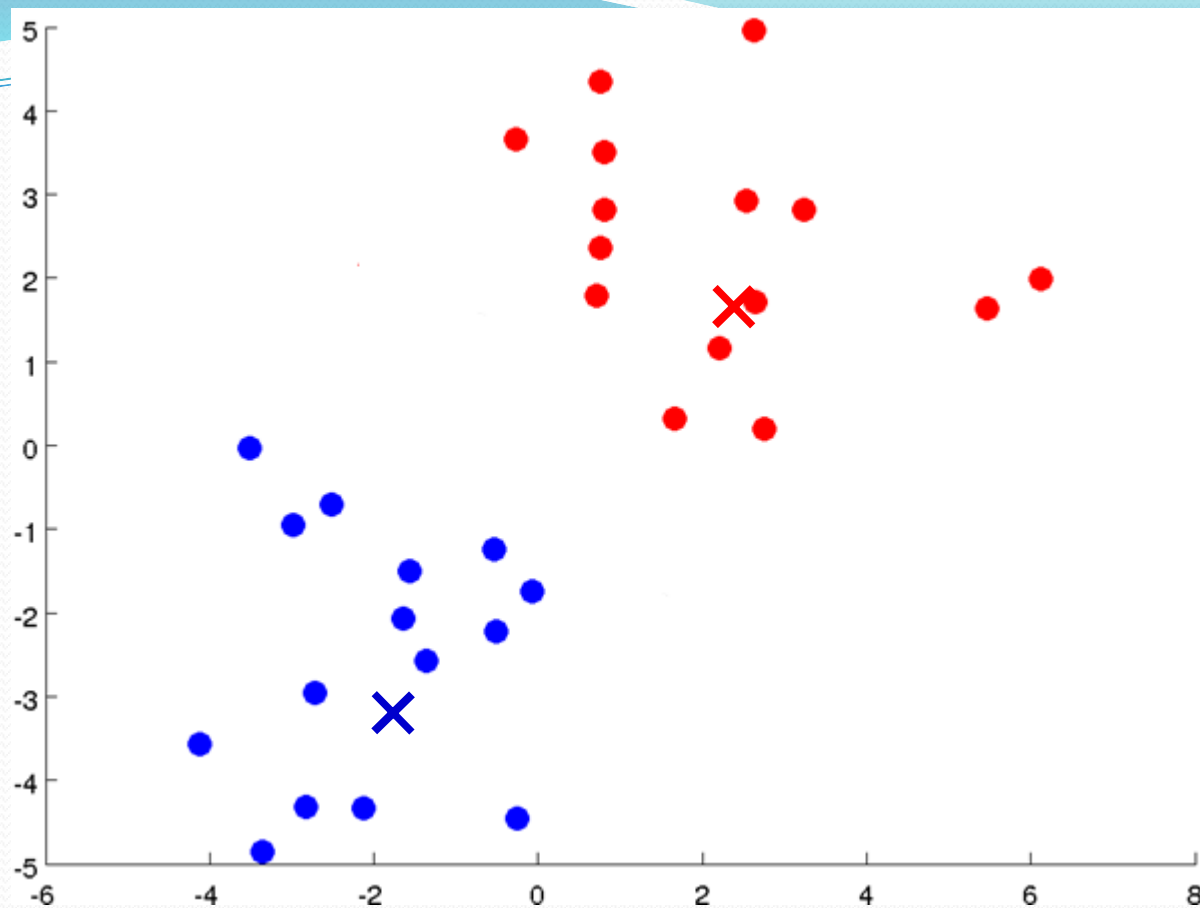












➤ If you keep running additional iterations of K means from here the cluster centroids will not change any further, so at this point, K means has converged

# K-means algorithm

Input:

- $K$  (number of clusters)
- Training set  $\{x^{(1)}, x^{(2)}, \dots, x^{(m)}\}$

$x^{(i)} \in \mathbb{R}^n$  (drop  $x_0 = 1$  convention)

## K-means algorithm

Randomly initialize  $K$  cluster centroids  $\mu_1, \mu_2, \dots, \mu_K \in \mathbb{R}^n$

Repeat {

  for  $i = 1$  to  $m$

$c^{(i)} :=$  index (from 1 to  $K$ ) of cluster centroid

    closest to  $x^{(i)}$

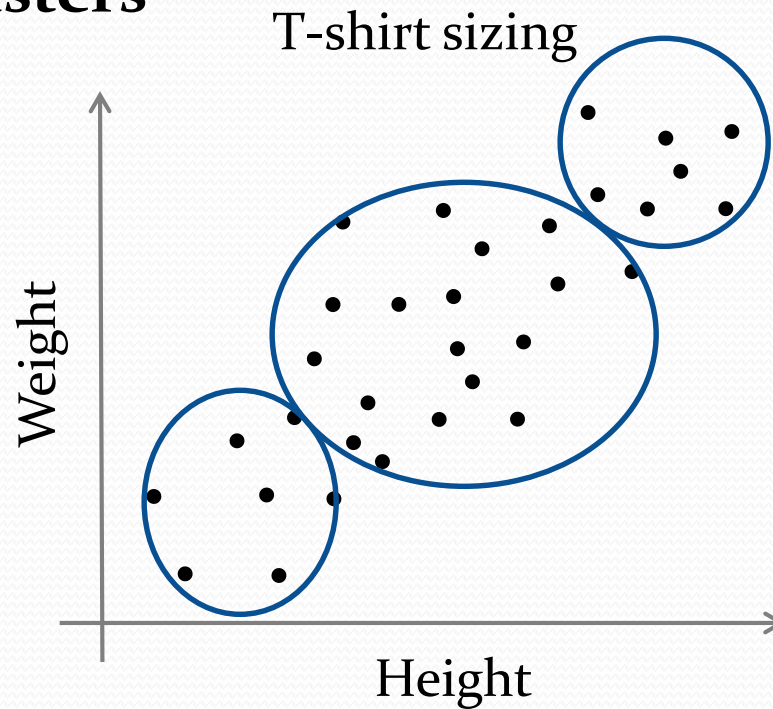
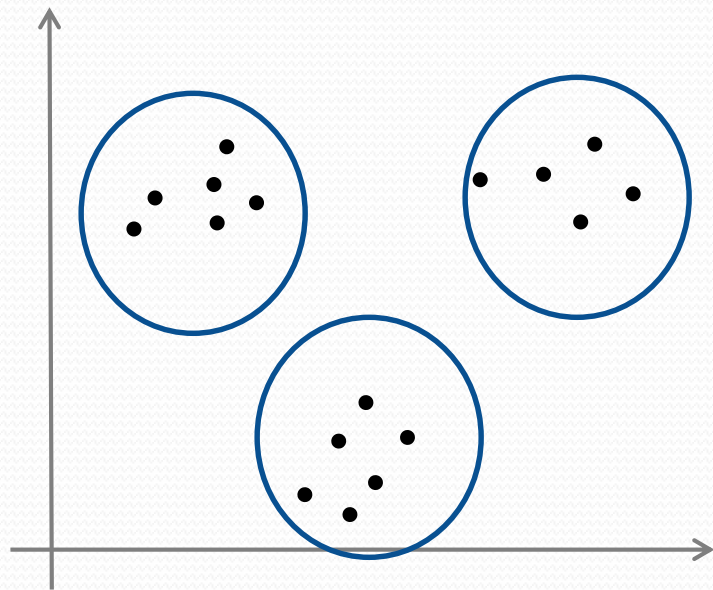
$$\min_k ||x^{(i)} - \mu_k||^2$$

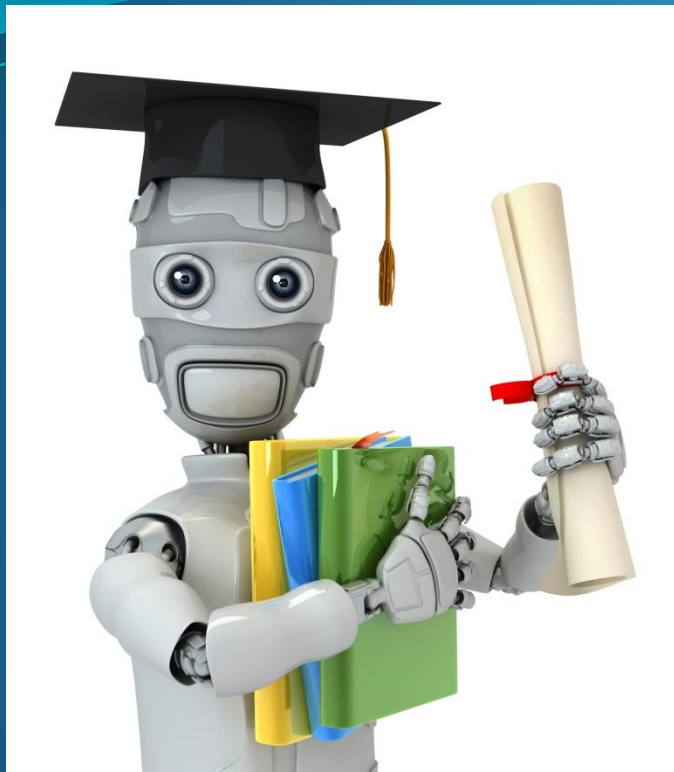
  for  $k = 1$  to  $K$

$\mu_k :=$  average (mean) of points assigned to cluster  $k$

}

# K-means for non-separated clusters





Machine Learning

# Clustering Optimization objective



## K-means optimization objective

$c^{(i)}$  = index of cluster  $(1,2,...,K)$  to which example  $x^{(i)}$  is currently assigned

$\mu_k$  = cluster centroid  $k$  ( $\mu_k \in \mathbb{R}^n$ )

$\mu_{c^{(i)}}$  = cluster centroid of cluster to which example  $x^{(i)}$  has been assigned

Optimization objective:

$$J(c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_K) = \frac{1}{m} \sum_{i=1}^m ||x^{(i)} - \mu_{c^{(i)}}||^2$$

$$\min_{\substack{c^{(1)}, \dots, c^{(m)}, \\ \mu_1, \dots, \mu_K}} J(c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_K)$$

## K-means algorithm

Randomly initialize  $K$  cluster centroids  $\mu_1, \mu_2, \dots, \mu_K \in \mathbb{R}^n$

Repeat {

    for  $i = 1$  to  $m$

$c^{(i)} := \text{index (from 1 to } K \text{ ) of cluster centroid}$   
            closest to  $x^{(i)}$

    for  $k = 1$  to  $K$

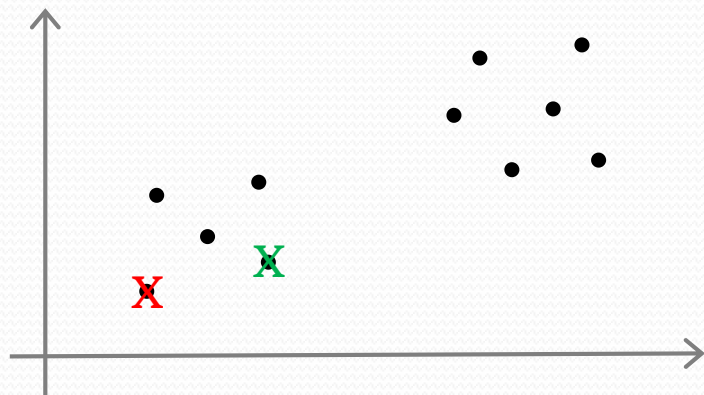
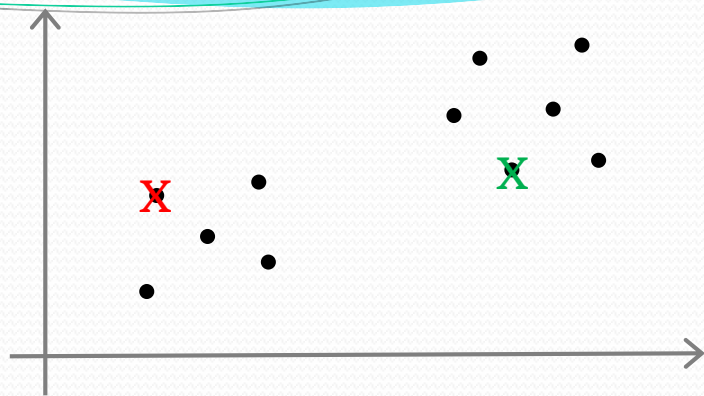
$\mu_k := \text{average (mean) of points assigned to}$   $k$

cluster

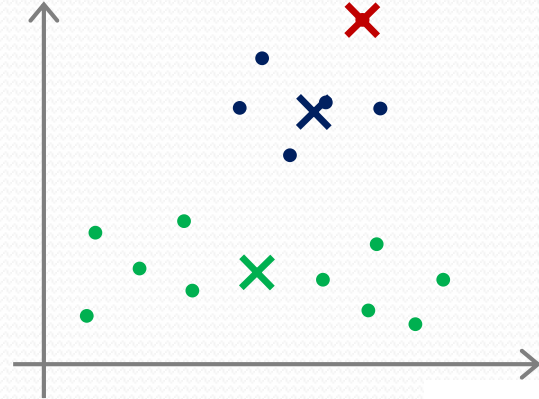
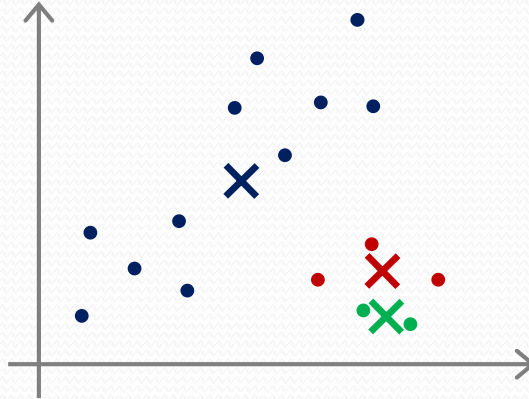
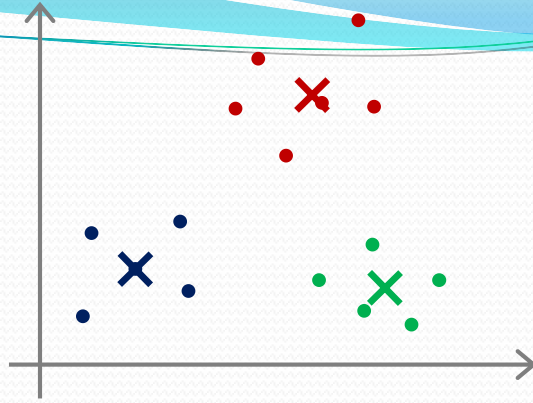
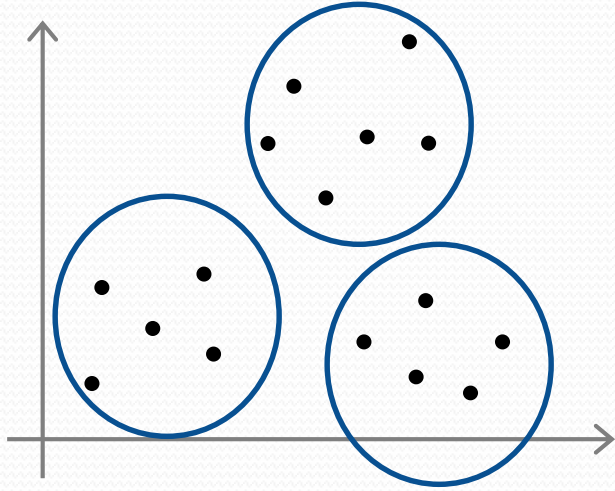
}

# Random initialization

- Should have  $K < m$
- Randomly pick  $K$  training examples.
- Set  $\mu_1, \dots, \mu_K$  equal to these  $K$  examples.
- By these two illustrations on the right. You might really guess that K-means can end up converging to different solutions depending on exactly how the clusters were initialized.



# Local optima



# Random initialization

For  $i = 1$  to 100 {

Randomly initialize K-means.

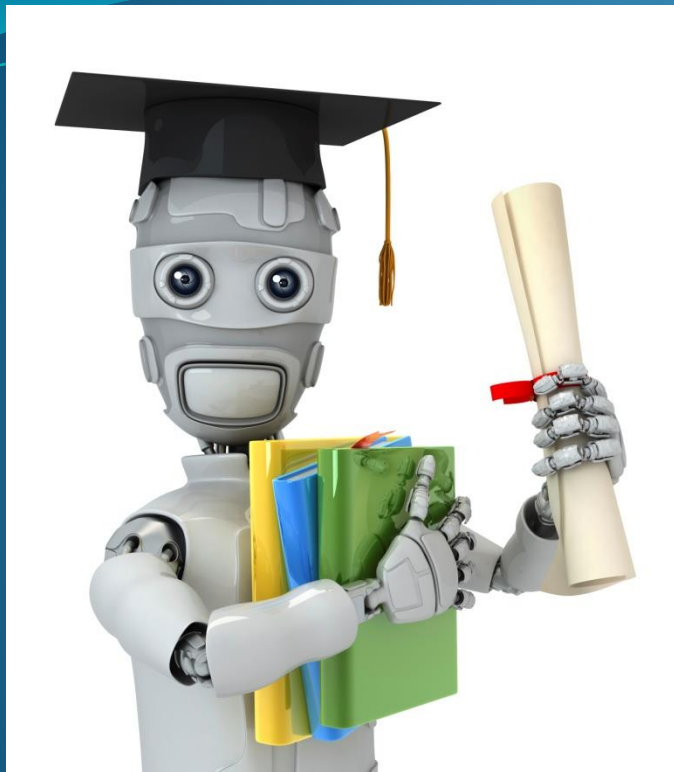
Run K-means. Get  $c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_K$ .

Compute cost function

$$J(c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_K)$$

}

Pick clustering that gave lowest cost  $J(c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_K)$



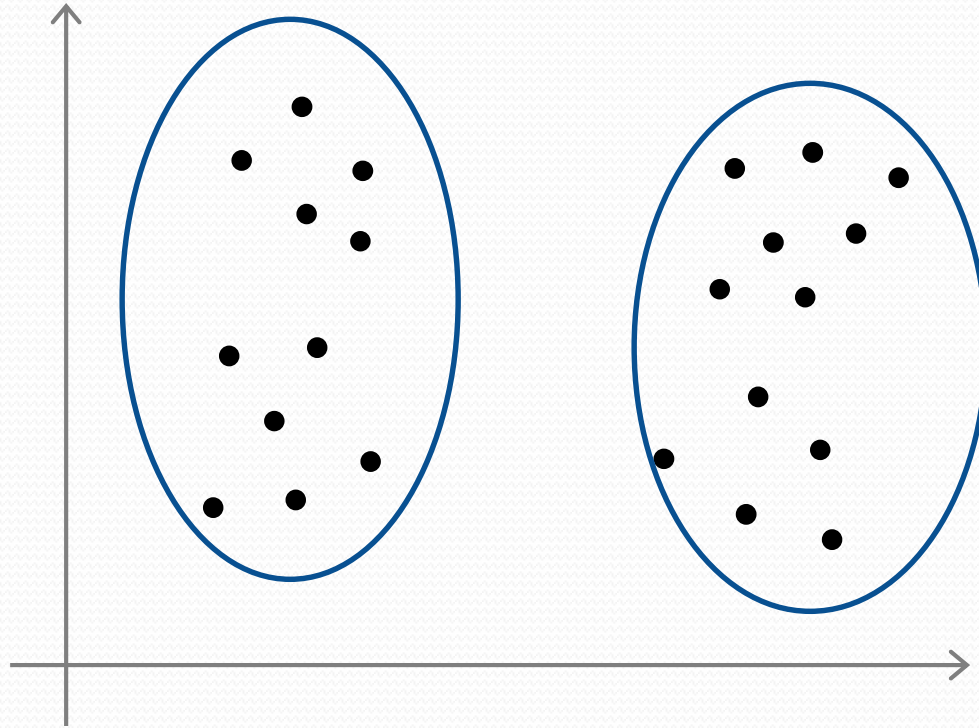
Machine Learning

# Clustering

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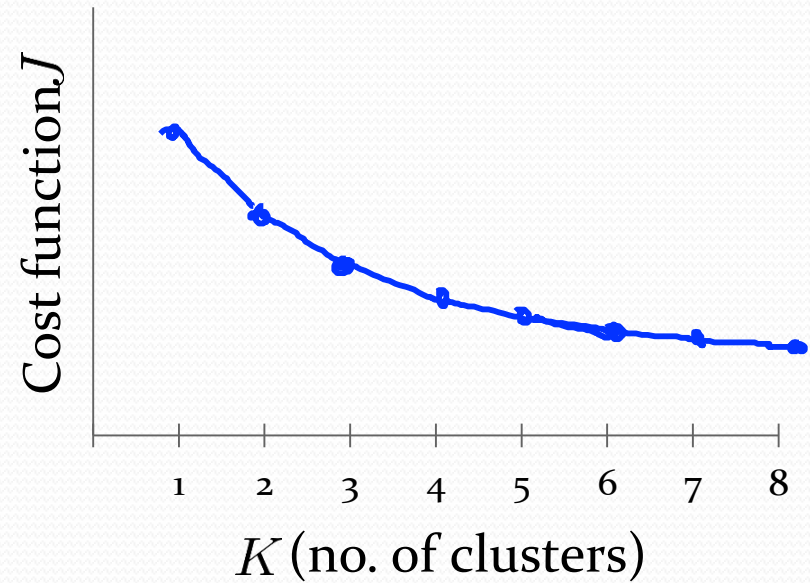
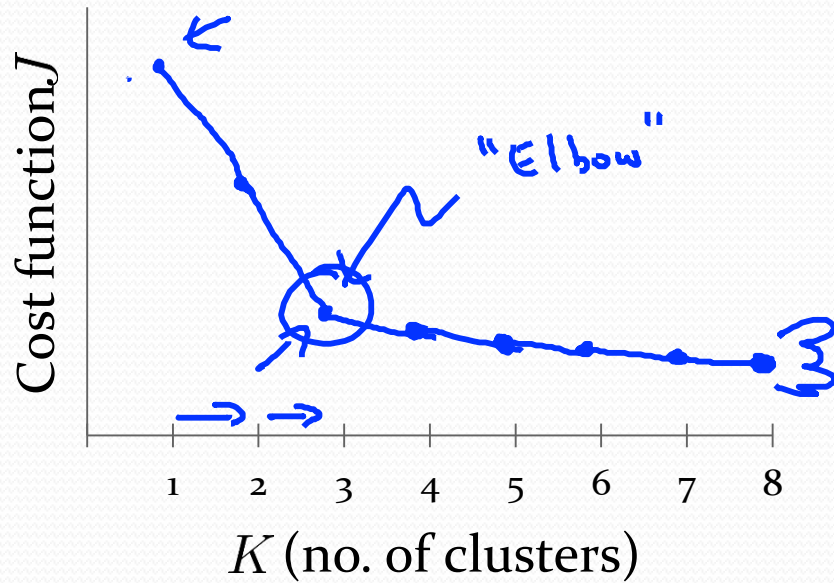
## Choosing the number of clusters

What is the right value of K?



# Choosing the value of $K$

Elbow method:

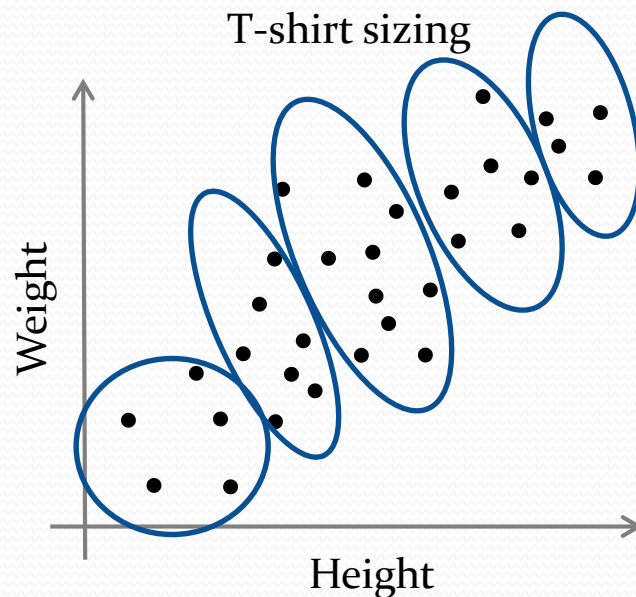
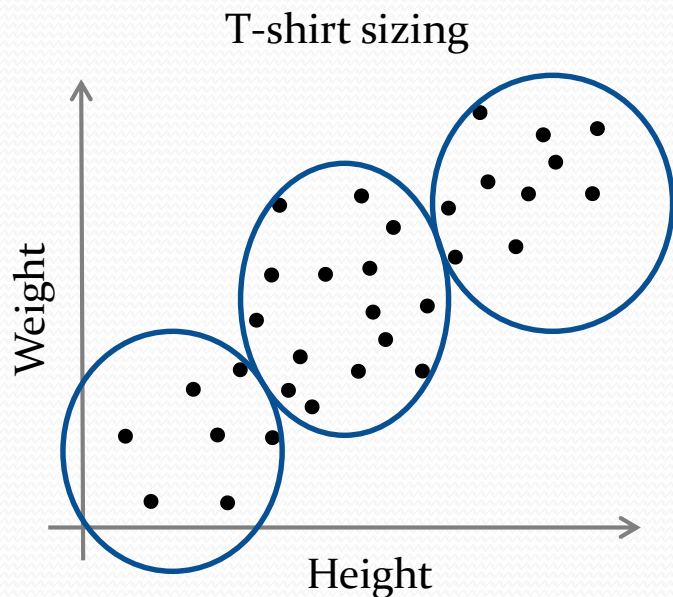




## Choosing the value of K

Sometimes, you're running K-means to get clusters to use for some later/downstream purpose. Evaluate K-means based on a metric for how well it performs for that later purpose.

E.g.





*Thanks*